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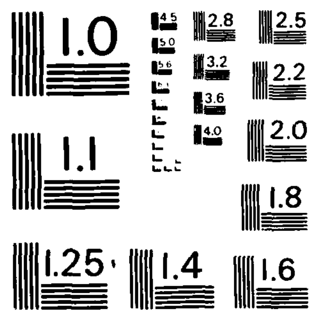

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IN SEARCH OF THE COMPONENTS OF TASK INDUCED JUDGMENT DECREMENTS

Betty S. Goldsberry

Rice University

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In Search of the Components of Task Induced Judgment Decrements

Betty S. Goldsberry

Abstract

Hammond's Cognitive Continuum Theory (Hammond, 1980) posits that three major categories of task features (content, structure, and presentation) determine how "analytically" or "intuitively" the individual will process information in arriving at a judgment. The state of the art does not permit a direct test of this basic assumption. However, some of its implications can be examined by manipulating the task features systematically and observing the effects upon both judgmental products and processes. This was the main purpose of the two experiments presented in this report.
The task format used in these experiments involved judging the suitability of hypothetical job applicants for various positions. An optimal model was available for integrating the predictive information so that actual selection outcomes (success, failure) could be simulated. Comparison of outcomes derived from human judgment with those derived from the optimal model provided an index of "product" quality; policy capturing techniques provided an index for "process" evaluation.

One content variable, the quantity of predictive information to be integrated, and one structural variable, the availability of an explicit integrative strategy, were combined factorially in a mixed design in experiment 1. The structural variable, availability, was manipulated more precisely (four levels of precision) together with a presentation variable, time permitted for judgment, in a similar mixed design in experiment 2. Key results indicated

that (a) human judgments were more accurate, relative to a theoretical optimum, when fewer than four items are to be integrated; (b) the decline in accuracy with quantity was reflected in process measures; (c) availability of an ideal weighting strategy did little to ameliorate the quantity effect--people do as well with a simple ordinal approach; (d) accuracy declined as a function of time pressure; (e) the four strategies reduced to two in actual use by the subjects, an equal-weighting and an ordinal-weighting policy; and (f) the superiority of the ordinal policy declined with time pressure. These results support various predictions from the Cognitive Continuum Theory and identify, for further exploration, a range of task conditions at the transition from primarily "intuition-inducing" to primarily "analysis-inducing."

INTRODUCTION

A common, critical, and rather intensively studied aspect of human decision making is diagnosis (or inference) based on equivocal evidence (Payne, 1982). How (and how well) people carry out this function is a central issue in the design of decision systems, ranging from personnel selection (Roose & Doherty, 1976) to medical diagnosis (Nystedt & Magnusson, 1975) to a host of military applications (Brady & Rappoport, 1973). If, as has been shown repeatedly, man's "intuitive" capability for using evidence is limited, it stands to reason that some form of "aiding" might help him produce judgments of consistently higher quality. And, indeed, a variety of aids such as "bootstrapping," Bayesian aggregation programs and the like have already appeared in operational systems (Slovic & Lichtenstein, 1971).

From a practical standpoint, of course, decision aiding is not without drawbacks. In some situations, for example, it is simply infeasible (e.g., the exigencies of battle often make timely access to a machine capability impossible). In others, it may be unnecessary (e.g., if the improvement in decision quality is not enough to justify the cost). And, even when it could be of value, users often mistrust machine aiding -- particularly if the resulting diagnosis is inconsistent with their own intuition. Add to these problems the growing suspicion that the case against human diagnostic capability may have been overstated (see, for example, Einhorn & Hogarth, 1981), and it becomes clear that the whole concept requires some rethinking. Aiding can obviously be of significant practical value; the question is, under what circumstances?

Several recent trends in decision research bear upon this issue. One is the redirection of attention from human deficiencies to task influences. People are neither purely "heuristic" processors of diagnostic evidence nor

optimal rule-followers. How they function depends to a great extent upon task features and, perhaps, upon individual differences as well (Payne, 1980). Therefore, it becomes important to consider how man's cognitive approach varies with identifiable task dimensions, and several current lines of research (including the present one) have been addressing this question.

Another trend, which is just now in its formative stages, is the blending of normative and descriptive approaches in the study of inference. For years the predominant emphasis was normative and axiomatic -- exploring human performance in terms of optimal models. Then it shifted to the descriptive and empirical -- cataloging the various forms of "heuristic" processing and their attendant biases (Slovic, et al., 1977). Each emphasis carried with it a different set of methods and issues. However, if one accepts the premise that situational features can dictate how the unaided human will approach a decision task and recognizes the obvious fact that some strategies will produce more favorable results than others, it becomes clear that description and prescription should proceed _together_. For example, it is useful to know that decision makers (DM's) attach certain weights to specific items of evidence in judging the qualifications of job candidates or in estimating the likelihood of enemy attack. However, these subjective weights take on far more practical significance when viewed against a theoretical optimum (i.e., the weights that produce the best prediction). Only then can we establish the practical _importance_ of whatever "human intuition" adds to or subtracts from the decision process. Only then can we begin to define the circumstances under which "biases" become sufficient to warrant decision aiding; but only if we have the descriptive data can we speculate on how best to implement aiding.

The present research was carried out in accordance with both of the above trends. Its purpose was to identify ranges along several generic task

dimensions within which the cognitive strategies (or decisions processes) used by DM's appear to shift and, at the same time, to establish the importance of such shifts for the decision product (i.e., the accuracy of decisions). The general framework upon which both task manipulations and expected cognitive influences were based was the Cognitive Continuum Theory (Hammond, 1980). In this view, DM approaches decision tasks intuitively (as in heuristic processing), analytically (as in rule-based processing), or at some intermediate point on a continuum joining these two extremes (i.e., "bounded rationality"). Where on this cognitive continuum he tends to operate depends on several principal dimensions of the task: (a) ambiguity of task content, (b) complexity of structure, and (c) form of task presentation. Highly complex, ambiguous, and time-constrained tasks, for example, promote intuitive processing, particularly if DM is not armed with the knowledge of optimal strategies or principles of task organization. On the other hand, simpler tasks (ones in which organization is clear, strategies are defined, and time pressure is minimal) tend to encourage the analytic mode. The specific task features that are presumed to define these three dimensions are reproduced in Table 1.

Since there is no convenient way to determine a priori exactly where on the continuum construct any set of task conditions should lie, it is difficult to submit the theory to rigorous test. Nonetheless, as a means of organizing the existing facts on human judgment and of suggesting promising research directions, the Cognitive Continuum Theory appears to have considerable merit. In particular, it suggests that manipulation of the decision task along specified dimensions (singly or in combination) should produce systematic changes in the judgment process and, as a result, changes in the decision product as well. Rarely in past research on judgment or decision making has

systematic change of this sort been examined within the context of the same basic task scenario. More typically, specific issues have been addressed using custom-made laboratory tasks -- ones designed to focus on judgmental heuristics, deviations from Bayes rule, nonoptimal choice, logical problem solving, and so on. By contrast, the Cognitive Continuum Theory encourages exploration of dimensions that cut across such task domains: from clearly defined to ill defined situations; from simple to complex structures; from time-stressed to more relaxed settings. Thus, it offers a coherent way of approaching the question raised at the outset: When do conditions warrant some form of aiding (and what judgmental processes are the most likely candidates for help)?

The present research involved manipulation of task variables from each of the major continuum-theory categories (see Table 1) and measurement of both the judgmental products of those manipulations and the processes by which the judgments were reached. The object was to determine how the accuracy and nature of a common type of judgment (cue-based prediction) change as conditions shift from a more "intuitive" to a more "analytic" position on the task continuum. At what point does unaided performance become seriously impaired, and when that happens, can the impairment be attributed to any particular aspect of the judgment process?

Two experiments were conducted, both using the same basic prediction task but differing in the particular combination of features manipulated. In the first, the <u>quantity</u> of predictive information (number of cues) and the <u>availability</u> of an explicit organizing strategy (scheme for weighting the cues) were varied; in the second, the <u>complexity</u> of the explicit strategy and the <u>time</u> available for using it were investigated. In both studies, performance was evaluated on the basis of how closely judgments approximated an

optimal organizing strategy. One measure, hit rate, was simply the percentage of occasions on which DM's prediction was the same as that produced by the optimal strategy. Another, achievement, was defined as the correlation between DM's judgments and those produced by the optimal strategy.

To examine the judgmental processes responsible for hit rate and achievement scores, it was necessary to compute three additional correlations. Although these require a bit of explanation, which is properly reserved for the next sections, suffice it to say here that they were indices of DM's reliability in judgment, his demonstrated understanding or knowle ge of the proper organizing rule, and his demonstrated ability to put is knowledge to use (or to control his judgments in a manner consistent with t rule). In other words, task conditions were manipulated so as to place sing demands on the unaided human DM -- demands which, at some point, would produce degraded performance (hit rate and achievement). By tracking reliability, knowlege and control as well as performance over these same conditions, it was hoped that the processes responsible for the decline could be estimated.

METHOD

Basic Task. The judgment task was chosen on the basis of its common usage in "policy capturing" research, and the likelihood that it would be meaningful for a wide variety of potential subjects. It consisted of evaluating the suitability of hypothetical applicants for a secretarial position using profiles of scores on nine-point skill ratings as predictors (or "cues"). In particular, subjects were required to integrate the profile information into a single suitability rating for each applicant by marking a nine-point graphic rating scale.

The target secretarial position was described in detail in a written job description. The profiles were constructed by random selection of ratings from normal disributions along each of the orthogonal skill dimensions. Both the normality and independence features were explained to the subjects (so that they would not be misled into searching for nonexistent profile structures). Although the information available for making suitability judgments varied with experimental conditions, subjects were required to do all calculations or other operations on the presented data mentally.

The key task manipulations were implemented by varying the number of skill ratings in each profile (the _quantity_ variable), the _time_ allowed for each evaluation, the presence or absence in the instructions of a specific rule for combining the skill ratings (the _availability_ variable), and the _complexity_ of that integrating rule. _Quantity_ and _availability_ were varied in the first experiment; _time_ and _complexity_ in the second.

Procedure and Measures. Each subject served for three 45 minute sessions scheduled approximately one week apart. At the beginning of each session, written instructions were presented describing the secretarial position, the employer company, the assessment procedure, and whatever strategy information was called for by the experimental condition. To insure full understanding, these instructions were augmented as necessary through verbal exchange. Following the instructions, a booklet was presented containing the 90 applicant profiles to be rated during that session (10 practice and 80 experimental profiles arranged one to a page), and the subject simply worked his or her way through the pages at a controlled pace, rating the suitability of each profile in order. After all judgments were completed, a questionnaire was administered probing the manner in which the subject perceived and approached the task.

As indicated earlier, profiles were constructed by orthogonal combination of ratings drawn from three, four, or five skill (cue) dimensions. These dimensions are identified in Table 2 together with an indication of which ones were used in the various conditions of the two experiments. In Exp.1, number of cues was an independent variable; hence, only those with an assigned weight were included in each specified condition (e.g., _typing skill_, _language proficiency_ and _clerical skill_ for the three-cue condition). In Exp. 2, the four dimensions designated by asterisks were used throughout.

In both studies, the subject's overall suitability ratings for the various profiles served as the basis for two sets of derived measures: product measures (hit rate and achievement), which indicated how closely performance approximated an optimuum weighting strategy; and process measures (_reliability_, _knowledge_, and _control_), which examined the cognitive elements underlying that performance. Computation of product measures requires definition of an optimal model relating cues (skill dimensions) to criteria. In other words, an "ecological validity" relationship must exist before one can study the human's proficiency in dealing with it. The model adopted in the present case was the standard linear regression approach commonly used in multiple-cue probability learning research. The weights assigned to the various cues in Exp. 1, for example, are shown in Table 2; those used in Exp. 2 are described in Table 4. _Hit rate_, then, was simply the proportion of a subject's suitability judgments that fell within a specified tolerance interval around the value generated by the optimal weighting rule. _Achievement_ was the correlation between the subject's and the model's ratings.

The process measures require a bit more explanation. Reliability refers simply to the subject's consistency in judgment and was indexed by the correlation between ratings made for the same sets of profiles early and late in each session. Knowledge, or the subject's understanding of the optimal rule, was indexed by the correlation between the optimal ratings and those produced by a model of the subject's "policy." The latter, of course, was derived from the subject's actual rating behavior through the use of linear regression to "capture" his (implicit) weighting rule (Dawes & Corrigan, 1974; Goldberg, 1974). Control was indexed by the correlation between judgments predicted on the basis of this "captured policy" and those actually produced by the subject in his profile ratings.

The distinction among these measures and the logic on which they are founded are perhaps best illustrated with reference to their original source: the Brunswik lens model (Brunswik, 1956; Hammond & Summers, 1972). As shown in Figure 1, Tucker (1964) suggested that the relationship (r_a) between judgments (Y_s) and criterion measures (Y_e, or the actual outcome of the events judged) can be partitioned into several statistically independent components reflecting respectively: (a) the subject's acquired knowledge of specific task properties, (b) his cognitive control in applying this knowledge, and (c) the degree of predictability in the task system. Tucker's complete equation reads as follows:

$$r_a = GR_s\ R_e + C\sqrt{1 - R_s^2}\sqrt{1 - R_e^2}$$

where

r_a = the correlation between correct (Y_e) and observed (Y_s) judgments;

G = the correlation between the linear prediction of the correct judgment (Y_e) and the linear prediction of the subject's judgment (Y_s) from the cue values;

R_s = the multiple correlation between the cues and the subject's judgments (Y_s), which is also the correlation between the subject's judgments (Y_s) and the linear predictions of the subject's judgments ($\hat{Y}_s$);

R_e = the predictability of the criterion (Y_e) from the cues in the task (which is also the correlation between the actual correct judgments (Y_e) and the predicted correct ($\hat{Y}_e$) judgments);

C = the correlation between the variance in the task system and the subject's judgmental system which is unaccounted for by G.

In the present case, this equation can be simplified to:

$$r_a = GR_s$$

since specification of an optimal organizing (weighting) strategy makes the criterion perfectly predictable from the cue values (i.e., $R_e = 1.00$), and the optimal strategy is linear (eliminating the need for the right-hand side of equation 1). Now, thus simplified, Tucker's equation renders the distinctions among measures used in the present experiments apparent. The r_a term represents <u>achievement</u> which, as we saw, can be decomposed into the two "process" indices: <u>knowledge</u> (G) and <u>control</u> (R_s). In words, a DM's judgments are accurate (<u>achievement</u>) to the extent that they correspond to the "true suitability" of the hypothetical secretarial applicants as dictated by our optimal model (e.g., Table 2). He can only be accurate if he understands this rule (<u>knowledge</u>) and is able to apply it (<u>control</u>) with consistency (<u>reliability</u>). By having indices of these three processes, we are in a position to probe the influence of the task conditions suggested by the Cognitive Continuum Theory.

EXPERIMENT 1

As indicated earlier, a task content variable, cue quantity, and a structure variable, rule availability, were manipulated in factorial combination. The purpose was to induce systematic shifts in performance which could then be analyzed using the process measures.

Subjects and design. Twenty-four undergraduate psychology students participated in exchange for extra course credit. Each was assigned at random to one of two groups defined on the basis of rule availability. The weighting group was provided with the specific numerical strategy used to generate the "optimum" ratings: the regression weights shown in Table 2 plus a description of how such weights should be used in making judgments (the linear weighting rule). The order group was told only that the cues were ordered in importance for the job of secretary as indicated in parentheses in Table 2. The quantity variable was manipulated within subjects at three levels: 3, 4, or 5 cues as shown in Table 2. Thus the design was a mixed model 2 x 3 factorial with 12 subjects per group.

Results. The principal findings for all measures are summarized in Table 3. Hit rate scores are based on a definition of accuracy in terms of a .2 cm tolerance interval around the optimal point on the graphic rating scale. All the other measures are in terms of correlations as defined earlier.

Considering first the overall (product) measures, both show the expected decline in performance as a function of the quantity of information to be processed (number of cues). However, the availability of an optimal strategy for weighting the cues (Group I vs. Group II) produced no apparent improvement over the simple ordinal instructions. These obvious trends were supported by an analysis of variance: quantity was highly significant for both hit rate and achievement, $F(2,44) = 18.69$ and 47.20 respectively, both $p < .001$; neither availability nor its interaction with quantity approached

significance on either index, $\underline{F}(1,22)$ was less than .35 in all cases. Since the same pattern of significance occurred on the process measures as well, all were collapsed across groups as shown at the bottom of Table 3; these results are presented graphically in Figure 2.

One important difference between the two product performance measures is the shape of the decrement over information quantity (see Figure 2). Achievement (Ach) scores declined linearly over all three levels while hit rate (HR) dropped only between the 3-cue and 4-cue levels. This pattern was supported by the Newman-Keuls test applied to pairs of conditions: the 3-4 cue difference was reliable for both measures ($p < .01$); the 4-5 cue difference was reliable for Ach ($p = .01$) but not for HR.

Turning to the process measures, it is apparent that knowledge (G) and control (C) were, in fact, the principal components in the overall Ach score. A multiple regression analysis showed that G explained 35% of the variance in Ach, C accounted for an additional 48%, and reliability (R) added less than 1% (a nonsignificant increment). The G component also contributed significantly to the overall hit rate (HR) score, accounting for 31% of the variance; the contribution of C, however, dropped to 7%, and that of R was again nonsignificant (at .4%). Looking at Fig. 2, it is easy to see how well GxC (the product of G and C) predicts the Ach function. One cannot, of course, "read" directly the relative contributions made by the components to the explained HR or Ach variance.

The data for each process measure were analyzed separately in the same fashion as for the product scores. Again, the ANOVA results showed a significant quantity effect for all measuresa: $\underline{F}(2,44) = 13.01$ for C, 57.66 for G, and 6.67 for R ; $p < .001$, .001, and .003 respectively. Neither availability nor its interaction with information quantity was significant

on any index: $\underline{F}(1,22) = 1.31$, $p < .265$ for G; $\underline{F} = (1,22) = 1.20$, $p < .286$ for C; $\underline{F}(1,22) = 1.57$, $p < .457$ for R. The Newman-Keuls analyses suggested that the 3-4 cue differences were reliable for all three indices ($p < .01$), but the 4-5 cue difference was limited to the G component ($p < .05$).

Despite the fact that R was also affected significantly by the quantity manipulation, the effect was not as systematic as in the case of the other process measures: for Group I, the 4-cue condition was inferior to the others; for Group II, the 5-cue condition was uniquely inferior. Since, as we have seen, this component accounted independently for very little variance in either product measure, it was not considered worthy of further interpretation. It is not surprising, of course, that R should add little unique predictiveness; in essence, both it and C should index DM's ability to apply his own weighting rule consistently.

Briefly, then, it appears that DM's ability to make integrative judgments declines as the number of cues increases, largely because he is less proficient at formulating an effective weighting policy (knowledge). Lack of a good strategy, of course, precludes maximum achievement. In addition, Ach appears to suffer from DM's inability to apply his own weighting strategy consistently (control). As one might expect, HR is not as predictable from cognitive process measures as is Ach; in fact the simple correlations between the two product measures only averaged $r = .48$. However, what predictability there is for HR rests almost entirely with the G component.

The fact that availability of an optimal weighting strategy did little to offset the decline in performance with information load is not surprising; if the detailed strategic information merely adds to an already heavy processing load, one would scarcely expect it to be of much help. At the lower information levels, however, one would expect some benefit. Absence of an

availability effect here could reflect either a ceiling limitation (an achievement score of around .90 may leave little room for improvement) or possibly a tendency for DM to reduce the metric weighting scheme to a simpler ordinal one (in which case the strategy would be identical to that for the "unavailable" condition). In view of this ambiguity, the rule availability manipulation was repeated -- and expanded -- in Exp. 2.

EXPERIMENT 2

In this study a task presentation variable (response time limitation) was examined in conjunction with a strategy manipulation. Here, however, a wider range of available weighting rules was used: the simplest (Note 1) consisted of four equal weights; the most complex (4), of four different weights. One rule (3) was identical to the 4-cue condition of Exp. 1. The expectation was that the more complex weighting schemes would encourage analytic processing, particularly under a liberal time limitation. However, with increasing time pressure, DM would be forced into a more intuitive mode and overall performance (hit rate, achievement) should suffer. As in Exp. 1, the plan was to examine the elements of any such overall decline using knowledge (G), control (C), and reliability (R) measures.

Subjects and Design. The 48 undergraduate volunteers were assigned randomly to four groups, each of which served under one of the weighting rules shown in Table 4. Each subject judged the same 80 applicant profiles under three different time limits (5, 10, and 15 seconds) with order of treatment balanced over subjects within each group. Order of profiles within each condition was randomized. Thus, the design was identical to that used in Exp. 1 except that the between-subjects variable (weighting rule) was manipulated over four rather than two levels.

Results. The principal findings are summarized in Table 5. For the

overall (product) measures, performance declined with both <u>time limitation</u> and <u>weighting strategy</u> complexity (if equal weighting of cues is considered the simplest rule). Both of these main effects were highly significant. In the case of the <u>weighting strategy</u> variable, the $\underline{F}(3,43) = 9.68$, $p < .001$ for HR, and 6.23, $p < .001$ for Ach; for <u>time limitation</u>, the respective values were $\underline{F}(2,86) = 11.98$ and 15.40, both $p < .001$. Despite the fact that the time limitation function appears steeper under the two simpler conditions (Groups I and II) than under the more complex ones (Groups III and IV), the interaction did not approach significance on either measure: $\underline{F}(6,86) = 1.15$, $p < .34$ for HR; 1.45, $p < .20$ for Ach. These functions are illustrated in Figure 3 (HR) and 4 (Ach) for the various strategy groups, and collapsed across groups in Figure 5.

Looking at Figure 3 and 4, it is apparent that the critical complexity level is the point at which either more or fewer than half the cues are to be weighed equally: the 3 and 4 cue levels produced similar performance that was generally superior to the 0 and 2 cue levels on both HR and Ach. Figure 5 shows that the time limitation was considerably more detrimental to HR than to Ach, particularly when fewer than 10 seconds was permitted. Overall, the correlation between HR and Ach scores was somewhat higher ($r = .62$) than in Exp. 1 ($r = .48$).

The G and C components again accounted for most of the variance in Ach (93%) and a significant, though considerably smaller, portion of that for HR (43%); while R added a nonsignificant 2% and 3%, respectively. Figure 4 shows that GxC (the product of G and C) again yielded almost perfect prediction of Ach in that the two lines on the figure coincide. While the pattern of variance in the two product measures explained by these components was not identical to that for Exp. 1, it was generally quite similar. That is, G

accounted for more of the HR variance, and C for more of the Ach variance (although both C and G plus their interaction contributed heavily to Ach), and these tendencies were greatest under the shortest time limitation (5 seconds). Unlike Experiment 1, however, C was the clearly dominant factor in both HR and Ach for the 15 second condition (it accounted for about five times the variance that G did on both measures).

The separate ANOVA's applied to the process scores indicated that time limitation had a significant effect on all three measures: $F(2,86)=22.02$ for C, 7.56 for G, and 8.99 for R; all $p < .001$. Strategy Complexity produced a reliable effect on two measures: $F(3,43)=3.88$, $p < .015$ for C; 14.37, $p < .001$ for G but only 2.32, $p < .088$ for R. More noteworthy than the main effects, however, was a significant interaction between the two variables for the C index, $F(6,86)=2.57$, $p < .024$. Looking at Table 5, it is clear that the interaction reflects an exaggeration of the time limitation effect under the presumably simplest equal-weighting condition. What this suggests is that the equal weighting rule can be applied very effectively if there is sufficient time; if not, the C index drops to a level below that for the "complex" unequal weighting rule. Neither the G nor the R measures showed an interaction between time limitation and strategy: $F(6,86)=1.38$ and 1.48 respectively, $p < .20$.

It is of some interest to compare the results for Group III under the 10 second condition (see Table 5) with those for Group II under the 4 cue condition in Exp. 1 (see Table 3) since they were, for all practical purposes, the same. The pattern across the various measures was quite similar; however, the absolute level of performance was uniformly higher in the present study. The only plausible explanation is that processing a fixed number of cues--even

with variable time constraints--is less confusing than having to integrate a variable number of cues.

Comparing the principal ways of varying task difficulty in the two studies (number of cues to be integrated vs. time in which to integrate them), it would appear that number tends to have a greater effect on the G component, and time, on the C component. That is, increasing the number of cues to be processed makes it harder for DM to formulate an appropriate strategy; reducing the time available makes it harder to apply his strategy consistently.

DISCUSSION

The research plan was to manipulate task variables in a manner designed to induce performance decrements and, by indexing concurrent changes in judgment processes, to identify the major components of those decrements. It was hoped that the information yielded by this approach would have implications for "decision aiding" in one common type of judgment task.

As expected, both increasing the amount of information to be processed (from 3-5 cues) and decreasing the available time (from 15-5 seconds per judgment) reduced the overall accuracy of DM's judgments (HR and Ach). Making the judgment rule more complex (unequal weights assigned to more than half the cues) also significantly reduced accuracy. Making it less explicit (ordering rather than weighting the importance of cues) had no effect, possibly because rank ordering is as precise as the human judge can be in this task. In any case, the two experiments provided ample opportunity for the study of induced decrements in judgment accuracy.

Two principal aspects of judgment were of interest: how closely DM's cue-weighting policy corresponded to the optimal rule (knowledge or G), and how consistently he was able to apply his own policy in making judgments (control or C). The latter concept was also indexed using a third measure (R), but

since it turned out to be largely redundant with the other two, it will not be discussed further.

The main finding with respect to these "process" measures was that different means of inducing decrements do, in fact, seem to operate through somewhat different cognitive mechanisms. In particular, adding to the information load (cues to be integrated) affects DM's ability to formulate an appropriate weighting strategy, even though the necessary information is provided explicitly. This is what one would expect if, in the language of Hammond's Cognitive Continuum Theory, the judge were to rely on an <u>intuitive</u> processing mode: "knowing" the proper rule does little to help him make better intuitive judgments because he is forced to use a simpler strategy. On the other hand, reducing the time available and/or increasing the complexity of the weighting rule seems to have a greater impact on the application than on the formulation of a proper weighting policy. Performance breaks down because DM has difficulty carrying out his own preferred strategy with any consistency. Over a large number of judgments, he may accord each cue its proper weight, but in a particular instance, he simply has trouble integrating the various cue values. Again, in Hammond's terminology, it is as though he were operating in a proper <u>analytic</u> mode, but was unable to do all the required mental calculations in the time allowed.

The above account is, of course, an oversimplification of the results--both G and C components were involved to an extent in most of the induced decrements. Furthermore, for reasons that are not entirely clear, performance was somewhat higher overall in Exp. 2 than in Exp. 1--even on identical conditions; hence direct comparisons between studies must be viewed cautiously. Nevertheless, the fact that different patterns of results emerged from the two studies, and they quite possibly represent different kinds of

Footnotes

1. Table 1 suggests that an equal weighting rule is simpler cognitively than an unequal one, although evidence for this assumption is sparse.

2. The G x C index is a predicted achievement score based on the product of obtained G and C scores.

processing deficits (albeit produced within the same basic task framework), is an encouraging finding. Future experimentation should, among other things, seek to replicate the time and quantity functions in factoral combination within the same study.

Should the present findings hold up under replication, it would suggest that system designers should focus on different aiding concepts depending upon how a particular task "stresses" the DM. For example, if he must deal with a large number of predictive items, some form of "divide and conquer" strategy might be most appropriate (to minimize the loss from "intuitive" simplification). If, on the other hand, time pressure is the main task demand, "bootstrapping" might be preferable.

The idea of tailor-making aiding concepts to generic task forms (diagnosis, action selection, etc.) is not, of course, new. What is suggested here, however, is that different concepts might be implemented within _the same basic task scenario_ depending upon which features are most troublesome. As the nature of the deficits produced by specific task dimensions becomes more clearly established, the plausibility of this approach to aiding can be subjected to more rigorous test.

Footnotes

1. Table 1 suggests that an equal weighting rule is simpler cognitively than an unequal one, although evidence for this assumption is sparse.

2. The G x C index is a predicted achievement score based on the product of obtained G and C scores.

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Table 1

Complexity of Task Structure

Inducing Intuition	Inducing Analysis
1. Texture of judgment scale	1. Texture of judgment scale
A. Many alternatives	A. Few alternatives
B. Many steps to solution	B. Few steps
2. Number of cues presented*	2. Number of cues presented
A. Many cues (5 or more)	A. Few Cues (2-4)
B. Contemporaneously displayed	B. Sequentially encountered
3. Vicarious mediation - Intra-ecological correlations large (R=.5) degree (horizontally)	3. Vicarious mediation - Intra-ecological correlations minimal degree (vertically)
4. Cue distribution characteristics	4. Cue distribution characteristics
A. Normal	A. Peaked
B. Linear function	B. Nonlinear, nonmonotonic function
5. Weights - equal**	5. Weights - unequal
6. Organizing principle - linear	6. Organizing principle - nonlinear

Ambiguity of Task Content

Inducing Intuition	Inducing Analysis
1. Organizing principle not available*	1. Organizing principle available
2. Task outcome not available	2. Task outcome available
3. Unfamiliar content	3. Highly familiar content
4. Feedforward	4. Feedforward
A. No training	A. Prior skill
B. No information	B. Information
5. Feedback - minimal	5. Feedback - cognitive feedback

Form of Task Presentation

Inducing Intuition	Inducing Analysis
1. Task decomposition - a posteriori	1. Task decomposition - a priori
2. Cognitive decomposition- a posteriori	2. Cognitive decomposition- a priori
3. Type of cue data - continuous	3. Type of cue data - dichotomous
4. Type of cue definition	4. Type of cue definition
A. Pictorial	A. Pictorial
B. Subject measures cue levels	B. Objective measures
5. Response time permitted or implied- brief**	5. Response time permitted or implied- open

* Manipulated in Experiment 1.
** Manipulated in Experiment 2.

Table 2

Rating Skills

Groups	Typing* Skill	Language* Proficiency	Telephone* Usage	Business Machine Knowledge	Clerical* Skill
Metric (Ordinal) Weights used in Exp. 1.					
3-cues	.5(1)	.3(2)			.2(3)
4-cues	.5(1)	.2(2)	.2(2)		.1(3)
5-cues	.3(1)	.2(2)	.2(2)	.2(2)	.1(3)

*Used in Exp. 2 as well.

Table 3

Mean Scores Obtained under the Six Experimental Conditions in Experiment 1 on All Five Measures

Experimental Condition	Measure: Product Hit Rate(%)	Product Ach.(r)	Process (r) Knowledge(G)	Process (r) Control(C)	Process (r) (GxC)	Process (r) Relia-bility(R)
Strategy Not Available (Group I)						
3 cues	49	.93	.98	.95	.93	.92
4 cues	38	.82	.89	.92	.82	.81
5 cues	36	.75	.83	.92	.76	.88
collapsed over quantity	41	.83	.90	.93	.84	.87
Strategy Available (Group II)						
3 cues	59	.89	.97	.92	.89	.87
4 cues	39	.79	.92	.85	.78	.85
5 cues	39	.73	.85	.85	.72	.77
collapsed over quantity	46	.80	.91	.87	.80	.83
Collapsed Over Groups						
3 cues	54	.91	.97	.94	.91	.90
4 cues	39	.80	.91	.89	.81	.83
5 cues	38	.74	.84	.89	.75	.83
collapsed over quantity	44	.82	.91	.91	.82	.85

Table 4

Weighting Strategies - Experiment 2

Skill Ratings	4 equal	3 equal	2 equal	0 equal
Typing Speed	.25	.40	.50	.40
Language Proficiency	.25	.20	.20	.30
Telephone Usage	.25	.20	.20	.20
Clerical Skill	.25	.20	.10	.10

Table 5

Mean Scores Obtained under the Twelve Experimental Conditions in Experiment 2 on All Five Measures

	Measures					
	Product		Process (r)			
Experimental Condition	Hit Rate(%)	Ach(r)	Knowledge(G)	Control(C)	(GxC)	Reliability(R)
4 Equal Wgt. Strategy (Group I)						
15 sec.	74	.94	.98	.96	.94	.94
10 sec.	71	.89	.98	.91	.89	.83
5 sec.	54	.83	.97	.85	.82	.72
collapsed over times	66	.89	.98	.91	.88	.83
3 Equal Wgt. Strategy (Group II)						
15 sec.	78	.95	.99	.96	.95	.93
10 sec.	70	.94	.98	.96	.94	.93
5 sec.	56	.91	.99	.92	.91	.86
collapsed over times	68	.93	.99	.95	.93	.91
2 Equal Wgt. Strategy (Group III)						
15 sec.	49	.91	.98	.93	.91	.88
10 sec.	48	.86	.97	.89	.86	.81
5 sec.	36	.87	.96	.87	.84	.79
collapsed over times	44	.87	.97	.90	.87	.83
0 Equal Wgt. Strategy (Group IV)						
15 sec.	44	.88	.98	.90	.88	.82
10 sec.	43	.88	.95	.93	.88	.90
5 sec.	41	.84	.97	.87	.87	.83
collapsed over times	43	.88	.97	.90	.88	.85

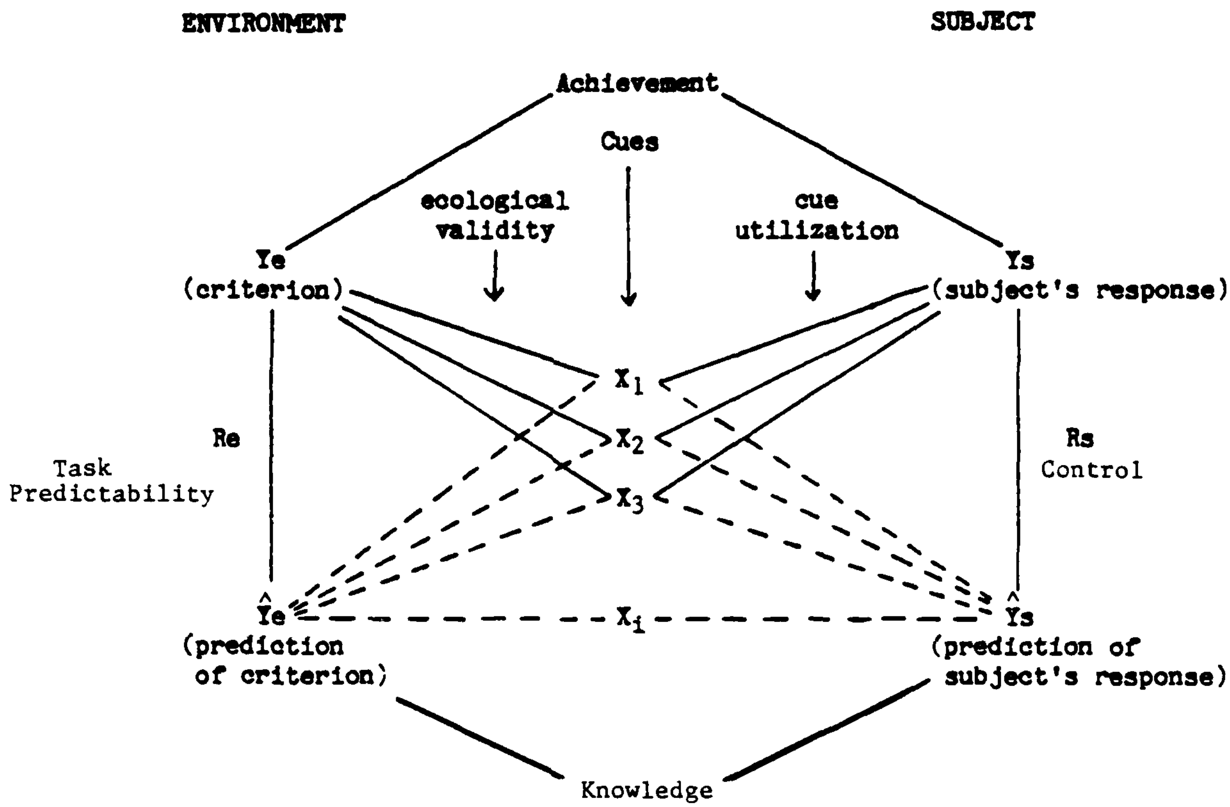


Figure 1. Brunswik's lens model.

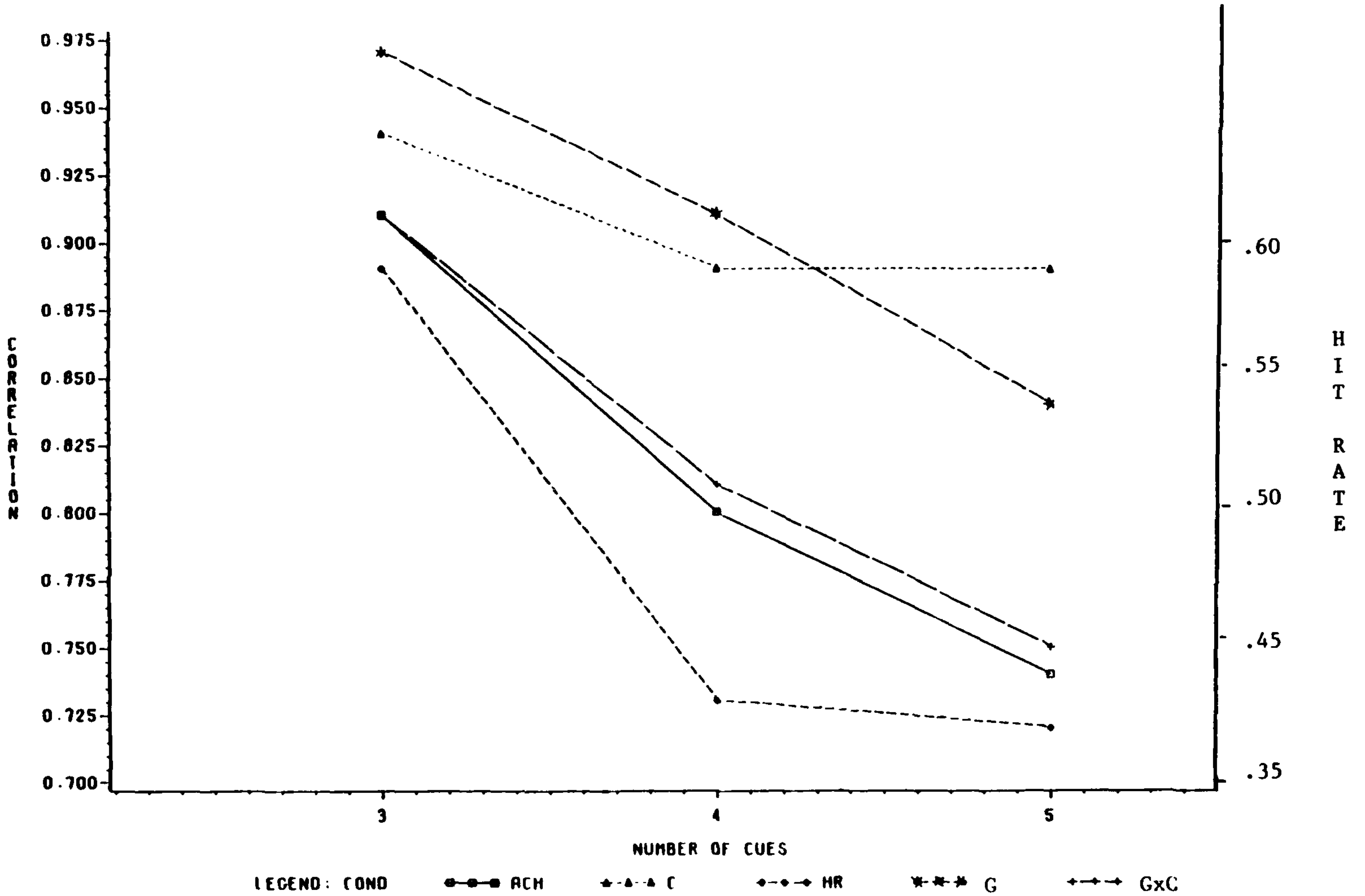
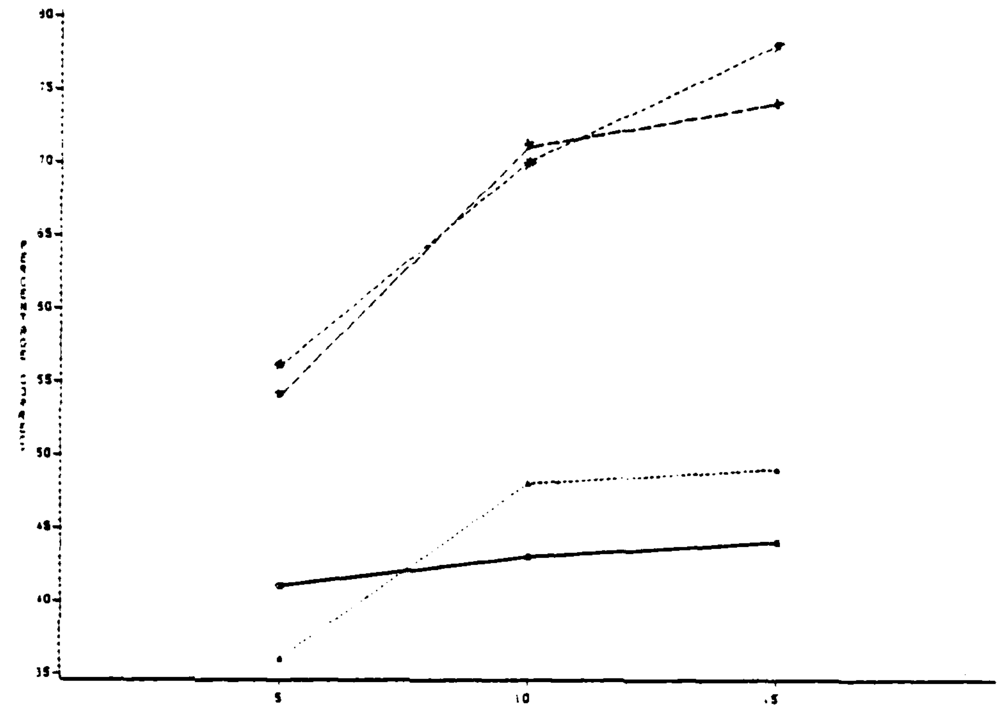
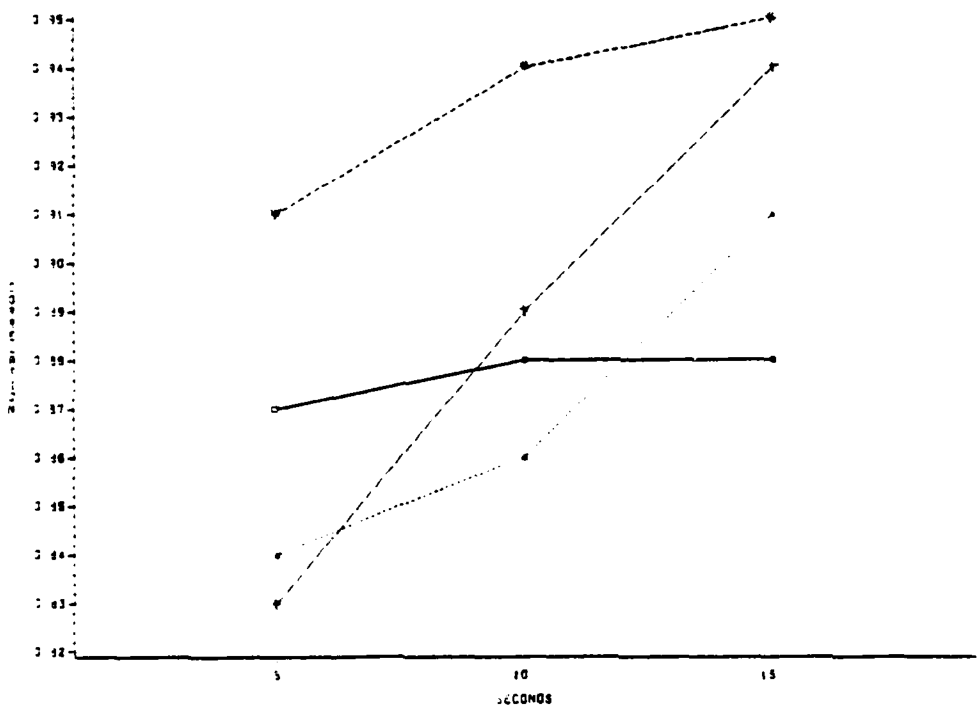


Figure 2: Information quantity functions for the main product and process measures collapsed over groups (note 2).



LEGEND: COND ——— 0EQ ····· 2EQ - - - 3EQ — — — 4EQ
FIGURE 3. EXPERIMENT 2 (HIT-RATE BY TIME INTERVAL)



LEGEND: COND ——— 0EQ ····· 2EQ - - - 3EQ — — — 4EQ
FIGURE 4. EXPERIMENT 2 (ACHIEVEMENT BY TIME INTERVAL)

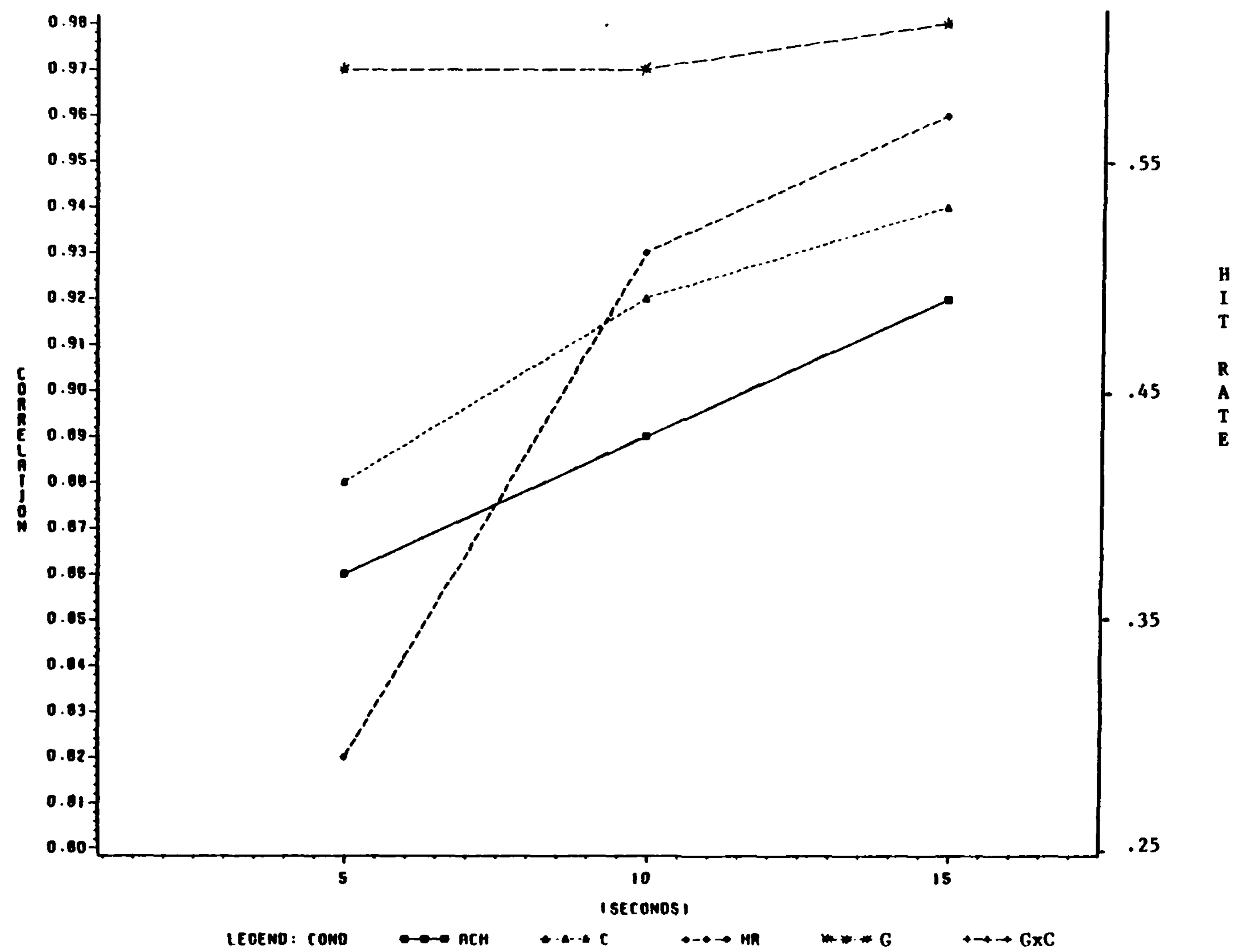


Figure 5: Time interval function for the main product and process measures collapsed over groups (note 2).

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